

Predictive modeling of performance of a helium charged Stirling engine using an artificial neural network

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ABSTRACT

In this study, an artificial neural network (ANN) model was developed to predict the torque and power of a beta-type Stirling engine using helium as the working fluid. The best results were obtained by 5-11-7-1 and 5-13-7-1 network architectures, with double hidden layers for the torque and power respectively. For these network architectures, the Levenberg–Marquardt (LM) learning algorithm was used. Engine performance values predicted with the developed ANN model were compared with the actual performance values measured experimentally, and substantially coinciding results were observed. After ANN training, correlation coefficients (R^2) of both engine performance values for testing and training data were very close to 1. Similarly, root-mean-square error (RMSE) and mean error percentage (MEP) values for the testing and training data were less than 0.02% and 3.5% respectively. These results showed that the ANN is an acceptable model for prediction of the torque and power of the beta-type Stirling engine.

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1. Introduction

Due to the rapid consumption of fossil fuels needed to meet the substantial energy requirements of today's world and the resulting environmental problems, many researchers have focused on finding alternative energy resources and developing new energy conversion systems. One topic of such research is the Stirling engine, which has a high thermal efficiency. It is an external combustion engine operated in a wide temperature interval, with possibilities for better combustion control. These engines operate on the principle of the compression and expansion (Stirling cycle) of several gases such as air, helium and hydrogen as working fluids [1,2].

The performance of Stirling engines depends on the physical and thermal properties (high thermal conductivity, high heat capacity and low viscosity) of the working fluid, the charge pressure, the temperature difference between the cold and hot ends, the heat transfer coefficient, the regenerator efficiency, the mechanical connections and the impermeability ratio [3].

Today, commercial companies and scientific institutions are continuing their efforts both experimentally and theoretically to improve the Stirling engine. The era of modern Stirling engine development was started in 1937 by the Philips Company of The Netherlands. Philips developed a number of Stirling engines of var-

ious sizes up to 336 kW [4]. Prodesser [5] constructed a Stirling engine using a biomass furnace heated with stack gas for generating electricity in rural areas. With this engine, a 3.2 kW output was obtained at 600 rpm under a charge pressure of 33 bars. Sripakagorn and Srikam [6] developed a prototype beta-type Stirling engine that worked at a moderate temperature range. At 773 K and 7 bar, the engine produced a maximum power of 95.4 W at 360 rpm. Karabulut et al. [7] presented the test results of a Stirling engine with a lever-controlled displacer driving mechanism using helium as the working fluid. The maximum torque and power were measured as 3.99 Nm and 183 W at 4 bars charge pressure and 533 K hot-end temperature. Cheng and Yu [8] developed a numerical model and applied it on a beta-type rhombic-drive Stirling engine. Non-isothermal effects, the effectiveness of the regenerative channel, and the thermal resistance of the heating head were taken into account by the model, and it proved to be capable of identifying the most crucial geometrical parameters affecting the engine's performance. Chen et al. [9] built a prototype helium-charged twin-power piston c-type Stirling engine. Some of its geometrical and operational parameters were investigated by a numerical model. Data taken from the prototype engine were used to correct the values of some factors in the numerical model. They found that regeneration effectiveness had the most prominent effect on efficiency, while engine speed had the greatest effect on the engine power within the range of the engine speed. Formosa and Despesse [10] obtained an analytical model that could be used to analyze Stirling engines, including their dead volume, imperfect

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regenerator, and external and internal thermal transfers. An analytical model was developed encompassing the critical flaws of the regenerator as well as the effectiveness of the heat exchangers.

As experimental studies are time consuming, and experimental sets very costly at present, different approaches such as genetic algorithms, finite elements models, fuzzy logic, ANN and the Taguchi method have been preferred in recent studies in order to minimize time and money spent on experimental studies. One of the most popular of these approaches is ANN. ANN is used in different applications in many scientific and other fields such as manufacturing, optimization, signal processing and especially in energy systems [11]. ANN was developed based on the working principle of the human brain. It can learn through examples and solve non-linear problems. ANN can be used for the solving of problems which are mathematically impossible or very difficult to model. A review of the literature shows that up to now no ANN model has been developed for estimating performance values of the Stirling engine. However, several scientific studies conducted on the prediction of performance values of other engine types can be found [12,13]. Yusuf et al. developed an ANN model for predicting performance values of a four-stroke dual-fuel single-cylinder diesel engine (diesel and natural gas) [14]. Results showed that the developed ANN model was a powerful one for predicting the performance values of a diesel engine. Ghobadian et al. developed an ANN model to estimate the performance of a two-cylinder, four-stroke diesel engine which was fuelled with biodiesel made from waste cooking oil and operated at different speeds. Performance values predicted by using the developed model were compared with experimentally measured values. As a result, R^2 values for the engine torque, specific fuel consumption, CO and HC emissions were found to be 0.9487, 0.999, 0.929 and 0.999, respectively [15]. Cay et al. [16] dealt with ANN modeling to predict the brake-specific fuel consumption (BSFC), effective power (Pe), average effective pressure (Ape) and exhaust gas temperature (Tex) of a methanol engine. Results showed that the ANN provided great accuracy in modeling the methanol engine performance, with R^2 equal to 0.9985, 0.9997, 0.9998 and 0.9992 for BSFC, Pe, Ape and Tex, respectively. ANNs were used to determine the effects of intake-valve timing on engine performance and fuel economy in research conducted by Golcu et al. [17]. Intake-valve timing and engine speed were used as the input layer; engine torque and fuel consumption were used as the output layer. For the torque-testing data, RMSE, R^2 and mean absolute percentage error (MAPE) were found to be 0.9017%, 0.9920% and 7.2613%, respectively. Similarly, the fuel consumption, RMSE, R^2 and MAPE were 0.2860%, 0.9299% and 7.5448%, respectively. Sayin et al. [18] dealt with ANN modeling of a gasoline engine to predict the brake-specific fuel consumption, brake thermal efficiency, exhaust gas temperature and exhaust emissions of the engine. Using some of the experimental data for training, an ANN model based on a standard back-propagation algorithm for the engine was developed. It was observed that the ANN model could predict the engine performance, exhaust emissions and exhaust gas temperature quite well, with correlation coefficients in the range of 0.983–0.996, mean relative errors in the range of 1.41–6.66% and very low root-mean-square errors. Atashkari et al. [19] first used group methods of data-handling type neural networks and evolutionary algorithms for modeling the effects of the intake-valve timing and engine speed of a spark-ignition engine on both developed engine torque and fuel consumption, using some experimentally-obtained training and test data. For the engine's torque-testing data, R^2 , RMSE and MAPE were found to be 0.999%, 0.325% and 3.09%, respectively. Similarly, for the fuel consumption, R^2 , RMSE and MAPE were 0.999%, 0.035% and 2.771%, respectively.

As shown in previous literary studies, ANN has a very wide range of usage [20–23]. However, the scientific literature is sparse

in terms of ANN applications on the performance of the Stirling engine. In this study, an ANN model was developed to predict the performance values of a beta-type Stirling engine using helium as the working fluid. The aim was to predict the engine performance (engine torque and power), taking into consideration the hot-source temperature (Hst), piston coating (Pc), compression ratio (r), charge pressure (Pch) and engine speed (N) at the input layer of the developed ANN model. The obtained ANN results are correct only for this Stirling engine and the developed model with its weighting coefficient is inapplicable for other engines or when the design of this engine is changed.

2. Materials and methods

2.1. Test engine

The technical specifications of the test engine, which are schematically shown in Fig. 1 and photographically in Fig. 2, are given in Table 1. The engine was made impermeable and able to resist a charge pressure of 8.5 bars. As can be seen in Fig. 1, the power cylinder and the displacer cylinder were placed on the same axis. The shaft output was mounted in the housing with bronze bushings; impermeability was ensured with sealing rings, using O-rings where required. The engine crankshaft was manufactured from AISI D3 cold-work tool steel as multipartite, and mounted in the housing with roller bearings. A static balancing procedure was performed, taking the weight of the connecting rods of the displacer and power piston into consideration. The power piston was produced from nodular cast iron. The power piston rings were made

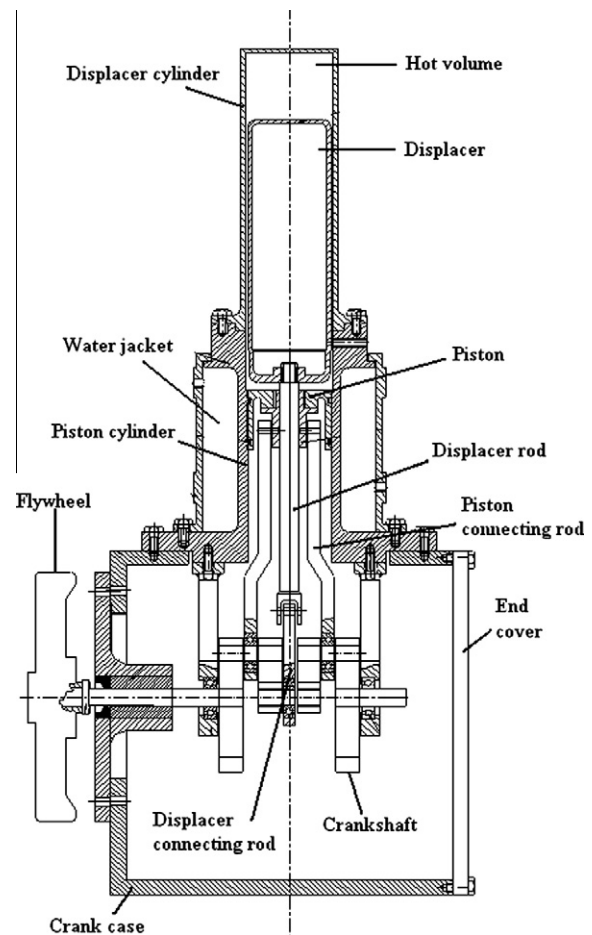


Fig. 1. Schematic illustration of the test engine.

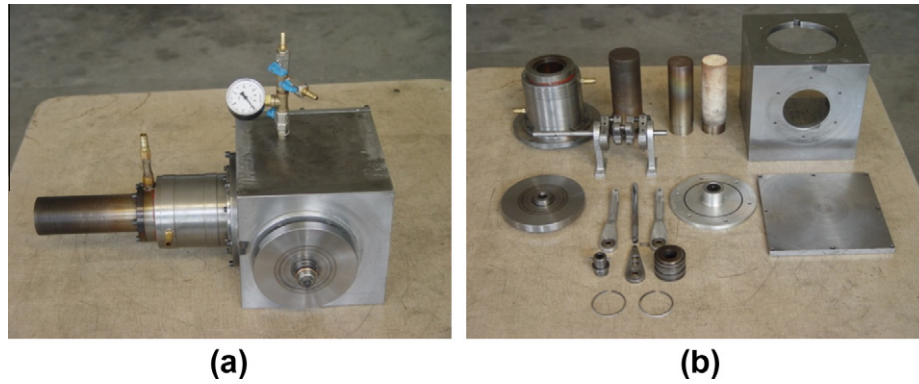


Fig. 2. Photographs of (a) the test engine and (b) its components.

Table 1
Technical specification of the test engine.

Parameters		Specification
Engine type		Beta
Power piston	Bore × stroke for 1.4 Cr (mm)	54 × 34
	Bore × stroke for 1.8 Cr (mm)	54 × 60
	Swept volume for 1.4 Cr (cc)	74.22
	Swept volume for 1.8 Cr (cc)	130.627
	Bore × stroke (mm)	54 × 60
Working fluid	Swept volume (cc)	137.41
		Helium
	Cooling system	Water cooled
	Compression ratio	1.4/1–1.8/1
	Maximum engine power	83.13 W (at 900 rpm)

of Teflon, with the ability to resist both friction and temperatures of up to 573 K. Two different displacers having the same dimensions were used in the experiment, as shown in Fig. 2b. Both of the displacers were made from chromium–nickel steel. One of the displacers was coated with 0.30 mm ZrO_2 as a thermal barrier, using the plasma spray method; the other displacer was uncoated. The coated displacer was manufactured 0.60 mm smaller than the nominal diameter, so there was no difference between the coated and uncoated displacers in terms of diameter. The cylinder was also honed. The connecting rods of the displacer and power piston were mounted in the housing with roller bearings in order to decrease friction. A working clearance of 0.03 mm was left between the power piston and the cylinder.

2.2. Experimental procedure

An adapted electrical heater, NUVE, was used to provide the heat needed to operate the engine. The heater was adjustable to temperatures between 273 K and 1473 K within an accuracy of 1 K. The hot end of the cylinder was inserted into the heater. To cool the cold end of the displacer cylinder, tap water was circulated in the water jacket of the engine. A Prony-type dynamometer with an accuracy of 0.003 Nm was used to measure the torque. The speed of the engine was measured by a digital tachometer (DT-2234A) with an accuracy of 1 rpm. A manometer equipped with a valve was used to control the charge pressure. Helium was employed as the working fluid. The experimental setup can be seen in Fig. 3.

2.3. Artificial neural network

ANN is a logic programming technique developed with the purpose of automatically performing skills such as learning,

remembering, deciding and inference, all features of the human brain, without receiving any aid [24,25]. The brain basically learns from experience. Some problems that are beyond the scope of current computers are indeed solvable by small energy-efficient packages. This brain modeling also promises a less technical way to develop machine solutions. This new approach to computing also provides a more graceful degradation during system overload than its more traditional counterparts [26]. ANN consists of parallel operations of processing elements called “neurons”. The design of these elements was inspired by the biological neural systems [27,28]. It is possible to train a neural network to perform a certain function by adjusting the values of weights between elements. In general, neural networks are trained, and output parameters corresponding to a certain input are obtained. Until the desired output parameter values are reached, the output and target are compared, and the training of the network (adjustment of weight values) is maintained.

ANN has three main layers, namely, the input, hidden and output layers. The input layer consists of data from the external world. Neurons at the input layer transfer data from the external world to the hidden layer. The data in the input layer do not process as the data in the other layers. The weights are numerical values of connections between cells. In the hidden layer, output is produced using data from neurons in the input layer and bias, summation and activation functions (Fig. 4). The summation function is a function which calculates the net input of the cell. The summation function used in this study is given in the following equation:

$$NET_i = \sum_{j=1}^n w_{ij}x_j + w_{bi} \quad (1)$$

where NET_i is the weighted sum of the input to the i th processing element, i and j are processing elements, n is the number of processing elements in the previous layer, w_{ij} is the weight of the connections between i th and j th processing elements, x_j is the output of the j th processing element and w_{bi} is the weight of the biases between layers. The activation function provides a curvilinear match between the input and output layers. In addition, it determines the output of the cell by processing the net input to the cell [30]. The selection of the appropriate activation function significantly affects the network performance. There are many ways to define the activation function, such as threshold function, step activation function, sigmoid function, and hyperbolic tangent function. The type of activation function depends on the type of neural network to be designed. A logistic sigmoid function is widely used for the transfer function [31,32]. The logistic transfer function of the ANN model in this study is given in Eq. (2). This transfer function takes the input (which may have any value between plus and minus infinity) and squashes the output into the range of 0 to 1 [33]. In the output layer,

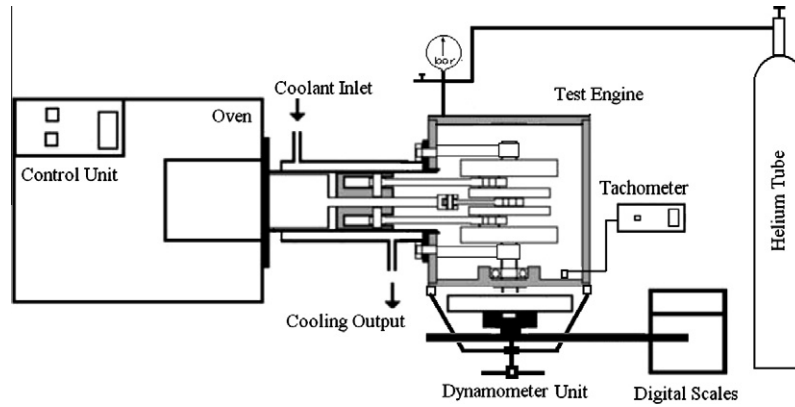


Fig. 3. Schematic view of the test rig.

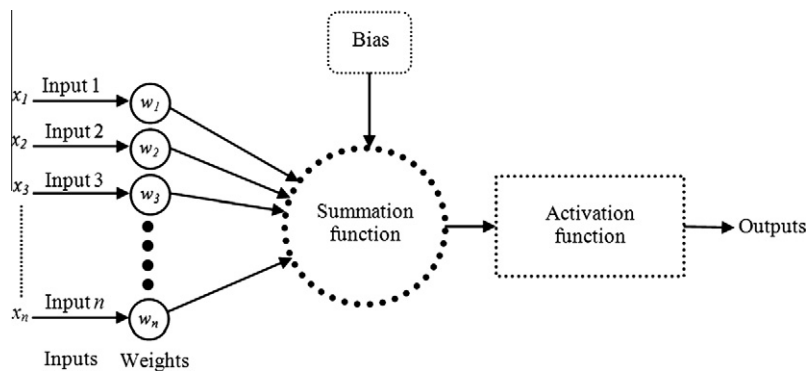


Fig. 4. The structure of an artificial neural cell [29].

the output of the network is produced by processing data from the hidden layer and sending it to the external world.

$$f(NEt_i) = \frac{1}{1 + e^{-NEt_i}} \quad (2)$$

There are various training algorithms that have been applied by previous studies, including Bayesian regularization (BR), Gradient descent with adaptive learning rule (GDA), Levenberg–Marquardt (LM), BFGS Quasi-Newton (BFG), Resilient back propagation (RP), Scaled conjugate gradient (SCG), Conjugate gradient with Powell/Beale restarts (CGB) and Polak–Ribière conjugate gradient (CGP) [34]. In this study, a computer program was developed on the MATLAB platform for training. The learning parameters of the proposed ANN structure are presented in Table 2.

The numbers of neurons in the input and output layers are based on the geometry of the problem. However, there is no general rule for selection of the number of neurons in a hidden layer and the number of hidden layers. Hence, they are determined by the trial-and-error method in this study. The best learning algorithm, optimal network structure and optimal number of neurons in the hidden layers were determined in order to acquire the closest output values to the experimental results. For this reason, both SCG and LM learning algorithms, network structures with single and double hidden layers, and different numbers of neurons in hidden layers were used in the determination of the optimal training parameters for the performance values of the Stirling engine. The determination of the best learning algorithm and optimal number of neurons for engine power are shown in Table 3.

After a number of trials, the best network architectures were 5-11-7-1 and 5-13-7-1 for torque and power respectively (Fig. 5). The

Table 2
The training parameters.

Training parameters	Engine torque	Engine power
Number of neurons in input layer	5	5
Number of hidden layers	2	2
Number of neurons first hidden layer	11	13
Number of neurons second hidden layer	7	7
Number of neurons output layer	1	1
Activation function	Log-sigmoid	Log-sigmoid
Learning algorithms	SCG and LM	SCG and LM
The normalization of data	0–1	0–1
Number of epochs	20,000–2000	20,000–2000

best results for both torque (T) and engine power (P) were predicted with the LM learning algorithm [35].

In the construction of the ANN architecture, 762 sets of data from the Stirling engine experiment were used in the training and testing process of ANN. In this study, training and testing data ratios were taken as approximately 90%:10% [36] as a reference. Therefore, 84 testing and 678 training datasets were randomly selected from all the experimental data. In ANN applications, data can be normalized in different ways. The most widespread method uses normalization procedures conducted between values of 0–1 [37] and 1 to –1 [38].

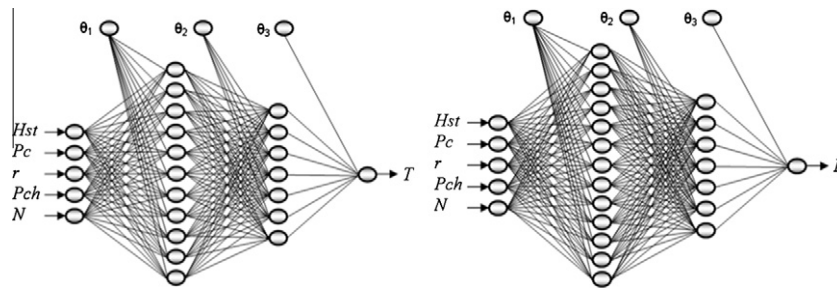
$$nv_i = 0.8 \times \left(\frac{v_{\min} - v_i}{v_{\min} - v_{\max}} \right) + 0.1 \quad (3)$$

The outputs were normalized between 0 and 1 using the formula in Eq. (3) [39]. Torque and engine power values predicted after ANN training were compared with the values from the experimental study. RMSE, MEP and R^2 values were used for

Table 3

Statistical data obtained using two different algorithms for the engine power.

Learning algorithm	Number of neurons	Training data			Testing data		
		RMSE	R^2	MEP	RMSE	R^2	MEP
SCG	5-7-1	0.024331	0.996213	6.176860	0.020005	0.997763	4.002299
SCG	5-9-1	0.021157	0.997142	5.352585	0.019030	0.997998	3.860739
SCG	5-11-1	0.020936	0.997198	5.112089	0.019814	0.997821	3.514199
SCG	5-13-1	0.020387	0.997347	5.077498	0.019375	0.997910	3.820023
SCG	5-15-1	0.021455	0.997056	5.390532	0.021619	0.997425	4.328297
SCG	5-9-5-1	0.019795	0.997502	5.062721	0.019935	0.997808	4.305024
SCG	5-9-7-1	0.017414	0.998067	4.273691	0.018943	0.998016	4.146133
SCG	5-9-9-1	0.017479	0.998053	4.204301	0.018336	0.998154	3.785060
SCG	5-11-5-1	0.019673	0.997531	4.994164	0.020021	0.997795	4.081798
SCG	5-11-7-1	0.017107	0.998135	4.161132	0.018000	0.998217	3.738729
SCG	5-11-9-1	0.017603	0.998023	4.363171	0.019169	0.997972	4.048280
SCG	5-13-5-1	0.018201	0.997888	4.448101	0.017411	0.998333	3.717643
SCG	5-13-7-1	0.016602	0.998244	4.079050	0.018205	0.998163	3.812225
SCG	5-13-9-1	0.017385	0.998074	4.330704	0.017918	0.998229	3.718908
SCG	5-15-5-1	0.019292	0.997626	4.639995	0.018376	0.998139	3.776752
SCG	5-15-7-1	0.016368	0.998293	3.977084	0.017382	0.998336	3.622911
SCG	5-15-9-1	0.014832	0.998599	3.613381	0.017250	0.998354	3.461567
LM	5-7-1	0.022629	0.996726	5.472668	0.021759	0.997348	4.506503
LM	5-9-1	0.021125	0.997146	5.293345	0.020799	0.997613	4.474031
LM	5-11-1	0.019623	0.997543	5.018361	0.020686	0.997618	4.399434
LM	5-13-1	0.020728	0.997258	5.308469	0.020042	0.997760	3.882647
LM	5-15-1	0.017610	0.998023	4.520727	0.017065	0.998395	3.884344
LM	5-9-5-1	0.015763	0.998417	4.075840	0.020625	0.997642	4.109922
LM	5-9-7-1	0.014704	0.998623	3.441094	0.021159	0.997499	3.904907
LM	5-9-9-1	0.013508	0.998838	3.401946	0.019854	0.997817	4.157176
LM	5-11-5-1	0.014270	0.998703	3.477267	0.018951	0.998020	4.050164
LM	5-11-7-1	0.013366	0.998862	3.215612	0.018972	0.998009	3.958269
LM	5-11-9-1	0.012080	0.999071	2.963242	0.019634	0.997873	3.964099
LM	5-13-5-1	0.013327	0.998869	3.458333	0.018726	0.998056	4.154044
LM	5-13-7-1	0.011822	0.999110	2.867979	0.018144	0.998179	3.498476
LM	5-13-9-1	0.010918	0.999241	2.652170	0.020906	0.997599	4.175261
LM	5-15-5-1	0.013396	0.998857	3.139635	0.022315	0.997238	4.267017
LM	5-15-7-1	0.010560	0.999290	2.516266	0.037417	0.992222	4.790259
LM	5-15-9-1	0.014371	0.998684	3.503254	0.016722	0.998462	3.767216

**Fig. 5.** ANN architectures with two hidden layer for torque and power of the Stirling engine.

comparison. The error identified during the learning process is called the root-mean-square error (RMSE) and is defined as follows:

$$RMSE = \left(\frac{1}{p} \sum_j |t_j - o_j|^2 \right)^{1/2} \quad (4)$$

where t is the target value, o is the output of ANN and p is the number of samples. The parameter t_j represents the predicted output from the neural network model for a given input while o_j is the desired output (i.e. exact data) from the same input that was produced by the setup. The mean error percentage, which shows the mean ratio between the error and the experimental values, is determined from:

$$MEP(\%) = \frac{\sum_j ((t_j - o_j)/t_j) \times 100}{p} \quad (5)$$

The absolute fraction of variance ranges between -1 and $+1$. R values closer to $+1$ indicate a stronger positive linear relationship, while R values closer to -1 indicate a stronger negative relationship [40]. This value is calculated with the following formula:

$$R^2 = 1 - \left(\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right) \quad (6)$$

3. Results and discussion

3.1. Experimental results

After mechanical and thermal problems were eliminated, the engine was run under several working conditions before

systematic testing. The engine power was measured at different engine speeds and charge pressures. Tests for compression ratios of 1.4:1 and 1.8:1 were performed with coated and uncoated displacers at hot-source temperatures of 1073 K, 1173 K and 1273 K. The power and torque values obtained at seven different charge pressures between 1 and 3.5 bars, with 0.5 bar increments, are given in Figs. 6 and 7, as well as the effect of charge pressures and hot-source temperatures on engine power and torque. The power output of the engine as well as the mass of the working fluid increased with the increase of the charge pressure, up to a certain value of charge pressure, and then declined. Optimum engine power and torque values were obtained at charge pressures of 3–3.5 bars. For all charge pressures, the engine power and torque increased with increasing hot-source temperatures since the heat transfer to the working fluid increased per cycle with increasing temperatures. The maximum power values for different hot-source temperatures and charge pressures for the compression ratio of 1.4:1 were approximately 18% higher than those for 1.8:1, as shown in Fig. 6.

The reason for the reduction of power at the charge pressure of 4 bar and compression ratio of 1.8:1 was the rise in the hydraulic resistance. Due to the increased mass-flow rate of the working fluid through the gap between the displacer and cylinder, the hydraulic resistance formed in the crankcase caused an increase of negative work and a decrease of engine power. Furthermore, the surface of the heater remained the same. Hence, the upper temperature of the cycle dropped with the increasing mass of working fluid, and the mass of working fluid was too much to heat or to cool in the limited time interval allowed by the engine speed at a charge pressure of 4 bar [41]. It was also noted that increasing the charge pressure resulted in an increase of vibration. Another reason for less engine power at the compression ratio of 1.8:1 was the shorter stroke with the compression ratio of 1.4:1, which caused less friction between the cylinder and the power piston. With the compression ratio of 1.4:1, the stroke of the power piston was 34 mm, whereas it was 60 mm with the compression ratio of 1.8:1. For this reason, more power was obtained with the compression ratio of 1.4:1. In addition, the connecting rod and ball bearing of the power piston had a rotation radius of 17 mm at the compression ratio of 1.4:1, whereas the rotation radius at the compression ratio of 1.8:1 was 30 mm. When the rotation radius is larger, the inertia forces that affect the crankshaft also increase. As inertia forces cannot be completely controlled with counter-weights, vibrations increase and affect engine power negatively.

At all testing stages, the power and torque values in cases where a ZrO_2 -coated displacer was used were higher compared to the

tests with an uncoated displacer, as shown in Figs. 6–8. The highest power and torque values were obtained at a hot-source temperature of 1273 K for all working parameters. At this temperature, the power increase provided by the coated displacer was 43% at the compression ratio of 1.4:1 and 60% at the compression ratio of 1.8:1 compared to the uncoated displacer. At the hot-source temperature of 1073 K, the power increase provided by the coated displacer became 24% at the compression ratio of 1.4:1 and 12% at the compression ratio of 1.8:1 compared to the uncoated displacer. The increase of power and torque was a result of reducing the shuttle-heat transfer. Reduction of shuttle-heat transfer enlarges the difference between upper and lower limits of the working fluid temperature. The reciprocating motion of the displacer between the hot and cold ends of the cylinder creates the shuttle-heat transfer. Most of the heat was transferred to the surface of the coating layer by radiation and convection during the flow process from hot to cold. The thermal conductivity of the coating material was lower than that of the metal from which the displacer was manufactured. Hence, heat accumulated at the surface of the coated displacer and increased its surface temperature. The heat was transferred to the working fluid by convection during the flow process from cold to hot, thus increasing the volume. As a result, the thermal efficiency, work generation and power of the engine increased per cycle [41]. This demonstrated that coating is more effective for larger compression ratios at higher temperatures than for smaller compression ratios at lower temperatures.

In Fig. 8 changes in power and torque values are given, according to the engine speed obtained with coated and uncoated displacers for the compression ratio of 1.4:1 and charge pressure of 3.5 and three different hot-source temperatures. While the engine speed increased, the torque decreased due to more and more decrease in heat exchange time with speed. The power increased with speed up to a certain level of speed and then declined. As the speed of the engine increased, inherently, the cyclic work decreased. This was caused by several factors, including the decrease of heat transfer between the working fluid and solid parts of the engine due to limited heating and cooling time, the increase of mechanical friction and viscous flow losses, the change of the circulation rate of the working fluid between cold and hot volumes, the increase of dissipative energy due to the vibration of the engine, etc. The engine power and torque increased as a function of the heater temperature. At a hot-source temperature of 1073 K, maximum power values were obtained at 500 rpm with the coated displacer and at 600 rpm with the uncoated displacer. At a hot-source temperature of 1173 K, maximum power values were obtained at 700 rpm with the coated displacer and at 800 rpm with

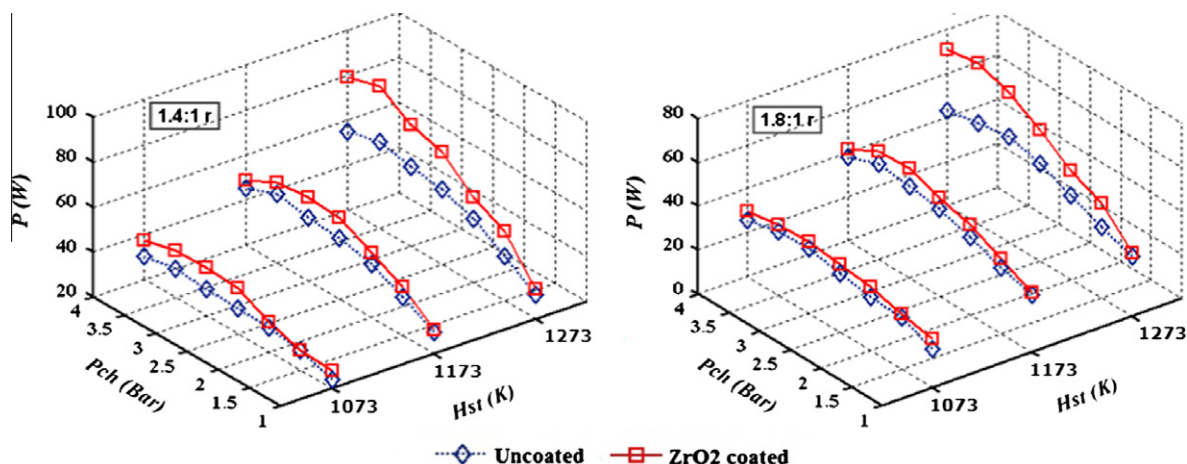


Fig. 6. Obtained power depending on charge pressures and heat source temperatures at 1.4:1–1.8:1 compression ratios.

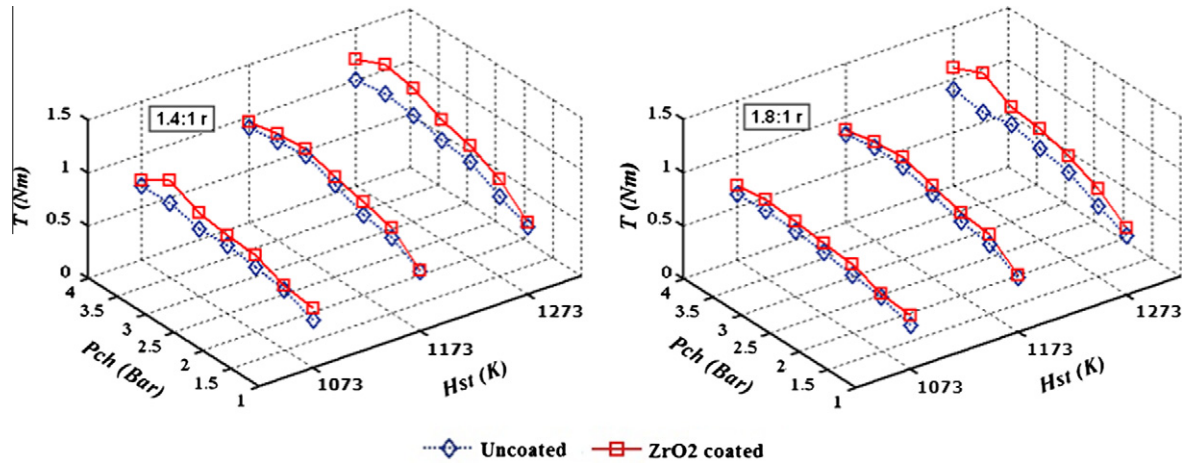


Fig. 7. Measured torque values depending on the charge pressures and heat source temperatures at 1.4:1–1.8:1 compression ratios.

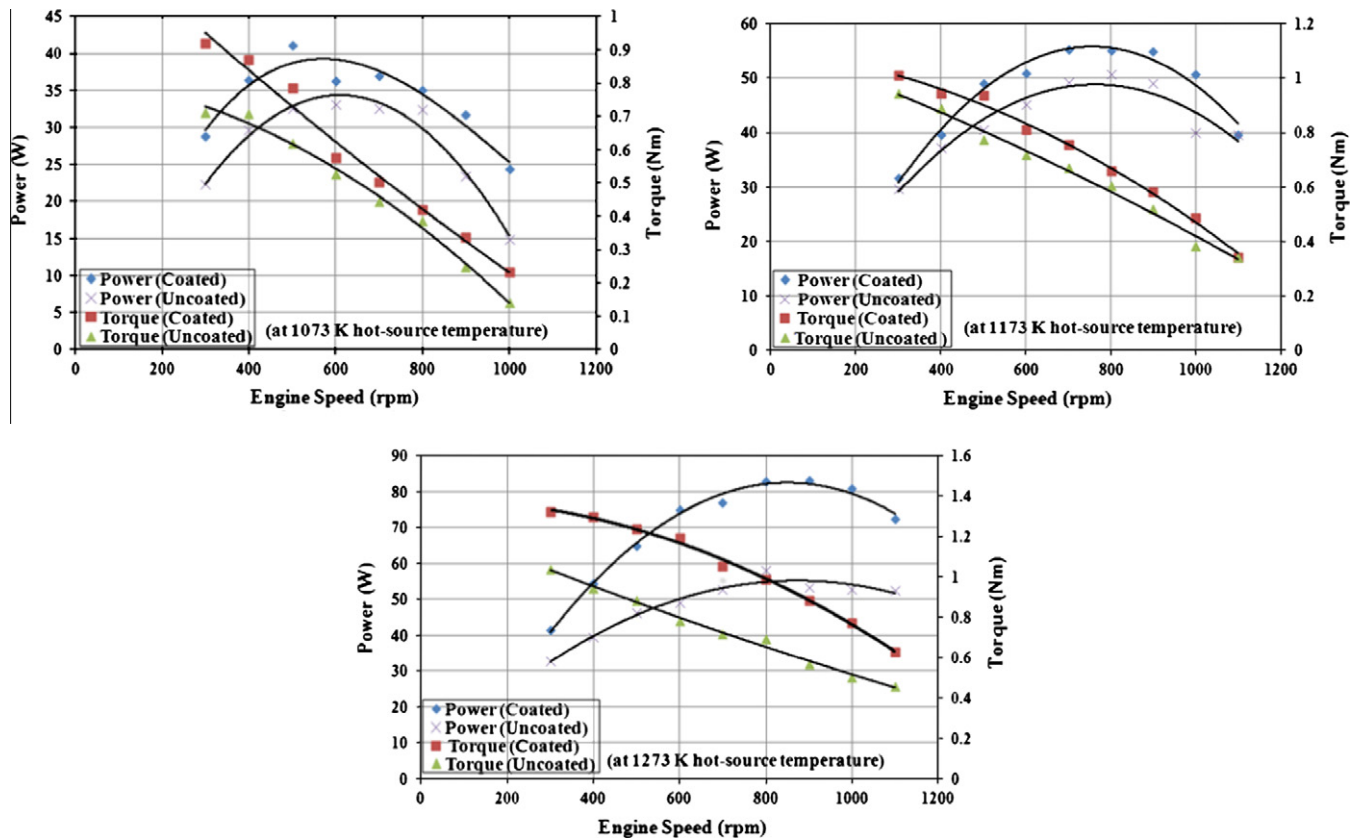


Fig. 8. Variation of power and torque depending on engine speed for 1.4:1 pressure ratio.

the uncoated displacer. Maximum power values were obtained at 900 rpm with the coated displacer and at 800 rpm with the uncoated displacer at a hot-source temperature of 1273 K. There is a linear relationship between the heater temperature and engine performance [7,42].

3.2. Multiple regression analysis

The multiple regression method is a statistical technique that allows us to determine the correlation between a continuous dependent variable and two or more continuous or discrete independent variables [43]. It can be used for a variety of purposes

such as analyzing experimental, ordinal, or categorical data. However, the analysis of variance (ANOVA) analyzes engine parameters which significantly affect the performance characteristics. In this study, ANOVA was used to determine the effects of process parameters on the engine torque and power of a beta-type Stirling engine using helium as the working fluid. The ANOVA results, as seen in Table 4, show that the effects of all Stirling engine parameters ($Pr < .0001$, $Pr < .0001$, $Pr < .0001$, $Pr < .0001$) on the engine torque and engine power are statistically significant. Mathematical statements established with multiple regression analysis for engine torque and engine power are given in Eqs. (7) and (8).

Table 4
Analysis of variance for torque and power.

Source of variance	Degrees of freedom (DF)	Sum of square (SS)	Adj (SS)	Mean square (MS)	F value	Pr > F	Percentage contribution (%)
<i>Engine torque</i>							
Hot-source temperature (Hst)	2	8.9236	11.3181	5.6590	1285.38	<.0001	41.78
Piston coating (Pc)	1	1.7962	2.3341	2.3341	530.15	<.0001	17.23
Compression ratio (r)	1	0.9074	1.4615	1.4615	331.95	<.0001	10.79
Charge pressure (Pch)	6	7.0784	8.4976	1.4163	321.69	<.0001	10.46
Engine speed (N)	9	24.0605	24.0605	2.6734	607.22	<.0001	19.74
Error	742	3.2668	3.2668	0.0044	–	–	–
C. total	761	46.0329	–	–	–	–	100
<i>Engine power</i>							
Hot-source temperature (Hst)	2	40519.3	45799.0	22899.5	601.27	<.0001	48.75
Piston coating (Pc)	1	5862.8	8851.8	8851.8	232.42	<.0001	18.84
Compression ratio (r)	1	5418.1	5711.7	5711.7	149.97	<.0001	12.16
Charge pressure (Pch)	6	34486.3	31146.3	5191.0	136.30	<.0001	11.05
Engine speed (N)	9	38927.7	38927.7	4325.3	113.57	<.0001	9.20
Error	742	28259.3	28259.3	38.1	–	–	–
C. total	761	153473.3	–	–	–	–	100

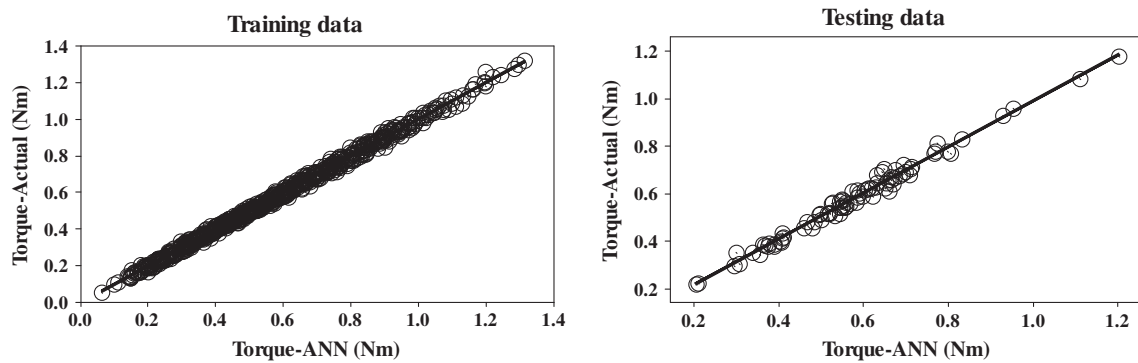


Fig. 9. The performance of ANN for engine torque.

Table 5
Statistical values for the Stirling engine.

Goal	Learning algorithm	Number of neurons	Training data			Testing data		
			RMSE	R ²	MEP	RMSE	R ²	MEP
Torque (T)	LM	5-11-7-1	0.011679	0.999349	2.411118	0.016046	0.998677	2.939651
Power (P)	LM	5-13-7-1	0.011822	0.99911	2.867979	0.018144	0.998179	3.498476

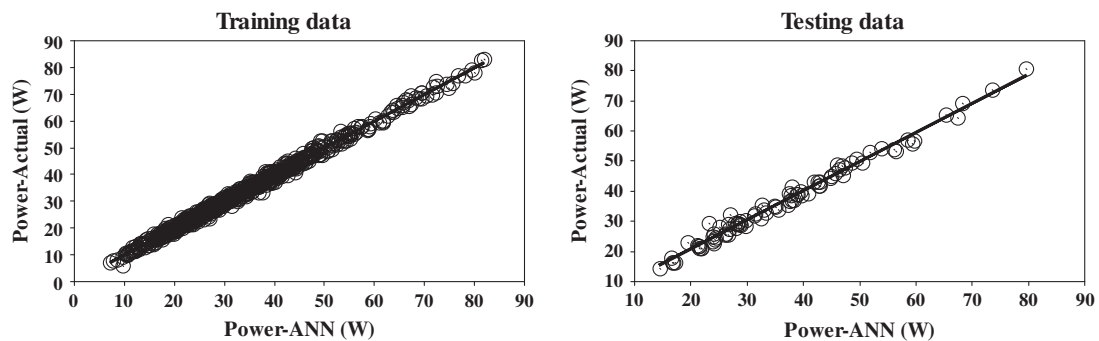


Fig. 10. The performance of ANN for engine power.

$$T = -0.390 + 0.00146 \times \text{Hst} + 0.0991 \times \text{Pc} - 0.213 \times r + 0.0967 \times \text{Pch} - 0.000635 \times N \quad (7)$$

$$P = -59.8 + 0.0893 \times \text{Hst} + 5.36 \times \text{Pc} - 12.6 \times r + 5.89 \times \text{Pch} + 0.0160 \times N \quad (8)$$

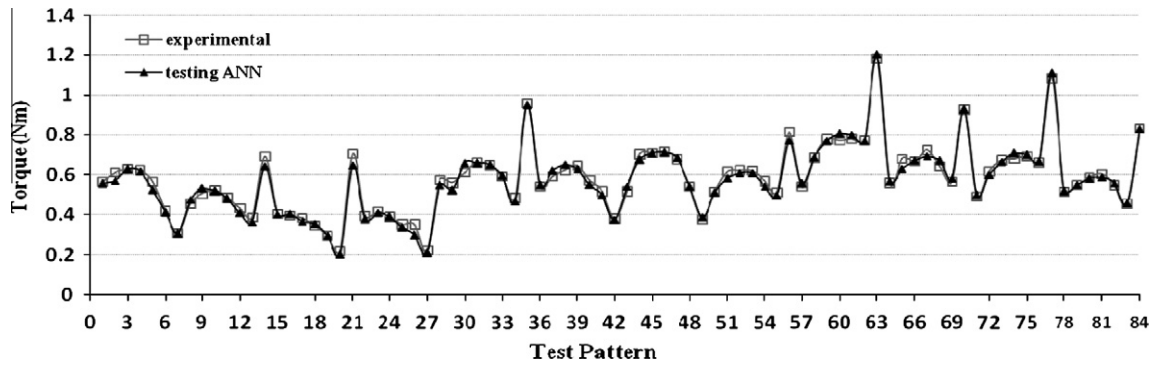


Fig. 11. Matching of the experimental and ANN values for testing sets of torque.

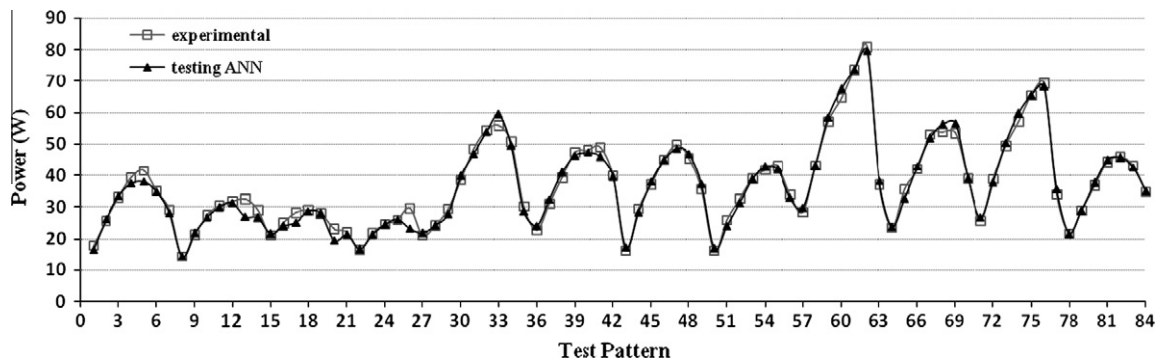


Fig. 12. Matching of the experimental and ANN values for testing sets of the power.

Table 6

Weights among layers for the Stirling engine torque.

$F_i = \frac{1}{1 + e^{-(w_1 \times N_1 + w_2 \times N_2 + w_3 \times N_3 + w_4 \times N_4 + w_5 \times N_5 + w_6 \times N_6 + w_7 \times N_7 + w_8 \times N_8 + w_9 \times N_9 + w_{10} \times N_{10} + w_{11} \times N_{11} + \theta_i)}}$												
<i>i</i>	<i>w</i> ₁	<i>w</i> ₂	<i>w</i> ₃	<i>w</i> ₄	<i>w</i> ₅	<i>w</i> ₆	<i>w</i> ₇	<i>w</i> ₈	<i>w</i> ₉	<i>w</i> ₁₀	<i>w</i> ₁₁	<i>θ</i> _{<i>i</i>}
Weights values between first and second hidden layers												
1	−21.4771	−51.2179	3.3048	−2.5362	0.0330	−1.2651	−0.3449	1.5737	0.6498	−0.0398	0.2500	22.7100
2	−17.3177	−144.8261	64.4189	−3.9569	−0.9681	−5.6612	2.4948	1.0063	−45.9673	−28.1228	0.4974	72.1641
3	34.2050	82.6791	−7.9666	−7.1297	1.4021	−4.9122	−2.5348	3.0982	0.9472	−0.4066	0.7530	−27.9569
4	1.6150	−15.4438	13.9270	19.6458	6.7571	14.0117	−5.3642	−8.9048	−2.0516	0.3669	−1.9830	−25.0248
5	1.6080	−24.7303	35.3800	0.3957	−4.4347	4.7259	2.8677	−0.0842	1.3067	−58.1757	−3.7018	−20.9758
6	−42.4592	6.3195	−15.5388	0.1874	15.5323	3.7110	3.2227	−50.4036	−3.7229	4.8917	−2.0657	47.1843
7	36.2164	−51.0334	36.5598	6.3426	−10.0729	13.4585	22.2690	3.7034	1.8060	2.3692	−0.8912	−61.7347
$N_j = \frac{1}{1 + e^{-(w_1 \times (W_t/1250) + w_2 \times (P_c/5.5) + w_3 \times (r/3.2) + w_4 \times (P_{ch}/4.5) + w_5 \times (N/1400) + \theta_j)}}$												
<i>j</i>	<i>w</i> ₁	<i>w</i> ₂	<i>w</i> ₃	<i>w</i> ₄	<i>w</i> ₅	<i>θ</i> _{<i>j</i>}						
Weights between input and first hidden layers												
1	5.9491	5.0614	−1.0967	−1.2060	−1.3678	−1.0050						
2	−4.0693	−3.4833	0.8042	1.0917	0.9937	−0.5955						
3	−2.9033	−3.1253	0.3697	1.2242	0.2818	1.8350						
4	1.5554	4.7165	1.4499	8.5726	4.0666	−7.5146						
5	−32.1844	−3.2027	−0.0787	40.0968	−4.2740	−0.9794						
6	5.4811	−2.8009	−0.4560	−10.1697	0.1273	0.5998						
7	−3.2557	2.2415	−0.6267	2.5250	−13.9790	1.3267						
8	29.3453	1.4597	1.8075	10.4140	0.3184	−27.9541						
9	−14.3017	33.0352	−3.9484	7.4236	1.0104	3.0696						
10	−5.3750	31.6506	0.1322	3.6288	−0.4702	−8.1754						
11	77.1310	−54.2158	12.4912	−10.9905	−15.0500	−26.2245						

Percentage contributions of hot-source temperature, piston coating, compression ratio, charge pressure and engine speed were 41.78%, 17.23%, 10.79%, 10.46% and 19.74%, respectively for engine

torque. In addition, percentage contributions of hot-source temperature, piston coating, compression ratio, charge pressure and engine speed were 48.75%, 18.84%, 12.16%, 11.05% and 9.20%,

Table 7
Weights among layers for the Stirling engine power.

$F_i = \frac{1}{1 + e^{-(w_1 \times N1 + w_2 \times N2 + w_3 \times N3 + w_4 \times N4 + w_5 \times N5 + w_6 \times N6 + w_7 \times N7 + w_8 \times N8 + w_9 \times N9 + w_{10} \times N_{10} + w_{11} \times N_{11} + w_{12} \times N_{12} + w_{13} \times N_{13} + \theta_i)}}$														
<i>i</i>	<i>w</i> ₁	<i>w</i> ₂	<i>w</i> ₃	<i>w</i> ₄	<i>w</i> ₅	<i>w</i> ₆	<i>w</i> ₇	<i>w</i> ₈	<i>w</i> ₉	<i>w</i> ₁₀	<i>w</i> ₁₁	<i>w</i> ₁₂	<i>w</i> ₁₃	<i>θ</i> _{<i>i</i>}
<i>Weights values between first and second hidden layers</i>														
1	−111.2370	−130.6790	−115.7398	122.2848	135.8736	112.4332	−10.8990	5.2137	−22.1738	−13.8794	−2.3713	11.5988	−36.5264	32.4129
2	−19.1434	20.0457	4.5088	−17.6514	−16.9607	0.2464	75.3018	0.7896	89.4059	−3.0470	−0.4484	−1.5339	−8.8473	−89.6631
3	−50.7252	−66.7834	−135.6605	110.1654	124.9508	128.9290	−56.4549	6.9322	−72.9728	−11.6899	−1.5768	11.5849	−28.5351	26.8769
4	67.0363	72.3208	−4.2213	−0.9176	2.0362	0.6271	−95.3176	−3.7347	−106.0838	1.6610	−0.0451	33.8508	12.4468	29.1313
5	57.5969	55.2429	−5.1541	26.1625	30.0954	3.7583	−87.1936	−2.3313	−96.6500	−0.4247	−0.4165	−10.0212	−5.0575	12.6126
6	75.7657	82.0033	−2.6401	−5.5754	−1.6480	−1.2759	−57.7051	−3.1722	−63.2137	6.8524	−3.1206	12.2096	20.0103	−21.4933
7	100.0795	72.5963	−0.3468	−8.3732	−9.7183	−0.7059	−28.9877	0.6516	−32.0503	−29.2919	−0.2872	3.4214	−65.7899	−7.7860
$N_j = \frac{1}{1 + e^{-(w_1 \times (Wt/1250) + w_2 \times (Pc/5.5) + w_3 \times (T/3.2) + w_4 \times (Pch/4.5) + w_5 \times (N/1400) + \theta_j)}}$														
<i>j</i>	<i>w</i> ₁	<i>w</i> ₂	<i>w</i> ₃	<i>w</i> ₄	<i>w</i> ₅	<i>θ</i> _{<i>j</i>}								
<i>Weights between input and first hidden layers</i>														
1	14.3368	6.0865	−0.2289	−6.8573	4.0478	−15.1191								
2	−13.7043	−6.4845	0.2846	5.9687	−3.7257	14.7568								
3	28.7586	9.5974	1.2408	−6.8359	−1.5451	−19.0748								
4	−0.4379	−1.9890	1.1282	−3.9185	−4.5598	4.9455								
5	0.3641	0.6288	−1.1128	3.4092	4.4069	−4.0291								
6	30.8763	37.3608	1.2082	−6.9885	−1.5099	−30.5475								
7	5.0531	5.8298	3.4716	−0.9294	−3.5307	−4.9862								
8	−10.1702	14.3665	−0.1049	−7.7081	5.1697	5.0315								
9	−5.2266	−5.5385	−3.1362	1.0385	3.4980	4.8070								
10	6.2006	−1.7803	−0.6285	4.7719	−8.9490	0.4378								
11	−6.2482	−82.5470	−0.7567	1.6615	4.6386	17.3829								
12	−11.0177	−9.7411	−2.3104	9.7427	3.9150	−1.4133								
13	1.0641	1.2727	0.2407	−1.5410	4.7102	−4.2885								

respectively for engine power. It can be understood from Table 4 that regarding the main effects, the greatest influence on the engine torque was exhibited by the hot-source temperature, followed by engine speed, piston coating, compression ratio and charge pressure. Based on the results of the analysis of variance, it can be seen that the greatest influence on the engine power was exhibited by hot-source temperature, then piston coating, compression ratio, charge pressure and engine speed.

3.3. ANN results

The test results and ANN predictions for torque are given in Fig. 9. The graphics clearly indicate that the predicted testing and training data were very similar to the engine test results. This case is also supported by the fact that the obtained R^2 values were very close to 1. In the ANN model developed for prediction of the Stirling test engine torque, RMSE values were calculated as 0.016046 and 0.011679 for testing and training, respectively. Average error values (MEP) for torque were found to be 2.939651 and 2.411118 for testing and training sets (Table 5).

Test results and ANN predictions for power are also given in Fig. 10. In these graphics, it can clearly be seen that both training and testing data results were very close to the experimental results. In the ANN model developed for prediction of the Stirling test engine power, RMSE values were calculated as 0.018144 and 0.011822 for testing and training, respectively. Mean error values for torque were found to be 3.498476 and 2.867979 for testing and training sets.

It can be said that the ANN approach developed for both engine torque and power presented the desired results. In Table 5, the obtained statistical values (R^2 , RMSE and MEP), optimal learning algorithm and network structure for the Stirling engine are given.

Matching experimental values and values predicted by ANN for testing sets of the torque and power are shown in Figs. 11 and 12 respectively; the predictive ability of the network for torque and power was very satisfactory.

Mathematical formulas belonging to the torque and power obtained by using the ANN approach are given in Eqs. (9) and (10). These formulas calculated the performance values of the beta-type Stirling engine without the need for any experimental work.

$$T = \frac{1}{1 + e^{-(23.7054 \times F1 - 61.4937 \times F2 - 8.6975 \times F3 + 1.8005 \times F4 - 32.0672 \times F5 - 0.7455 \times F6 - 1.2902 \times F7 + 50.4831)}} \quad (9)$$

$$P = \frac{1}{1 + e^{-(10.3299 \times F1 + 208.8583 \times F2 - 10.3107 \times F3 - 7.3215 \times F4 + 2.5866 \times F5 + 6.1503 \times F6 - 241.2799 \times F7 - 1.0643)}} \quad (10)$$

Weight values obtained for torque and power are given in Tables 6 and 7 respectively. The best results for both engine torque and power were obtained with double-hidden layer network architectures. For this reason, two separate weight tables were formed. The weight values between the input layer and the first and second hidden layers for torque are shown in Table 6. The weight values between the input layer and the first and second hidden layers for engine power are shown in Table 7.

4. Conclusions

In this study, an ANN approach was developed using the experimental findings obtained as a result of the testing of a beta-type Stirling engine at different operating parameters. The tests were conducted using coated and uncoated displacers. The rotation and power of the engine increased depending on the temperature of the heater. The temperature of the heater was increased up to 1273 K, which was close to the resistance limits of the material

used in the hot end of the engine. Tests conducted at this temperature resulted in the highest engine torque and power. Maximum torque and power were recorded as 1.32 Nm at 300 rpm and 83.13 W at 900 rpm; these were obtained with a coated displacer at a charge pressure of 3.5 bars, a hot-source temperature of 1273 K and a compression ratio of 1.4:1. An important finding was that the use of a ZrO_2 -coated displacer resulted in a substantial increase in torque and power. An additional finding was that the most significant factor affecting both torque and power was the hot-source temperature.

The back-propagation algorithm was used for training the ANNs developed for determining the performance values of the Stirling engine. The validity of the established ANN model was confirmed by comparing the ANN predictions with the experimental results. In addition, one of the classical modeling techniques, a multiple-regression method, was used to evaluate the prediction capability of the ANN. While the R^2 values for the torque and power obtained from the multiple-regression method were 92% and 81% respectively, in the ANN model, R^2 values for both the training set and the testing set of torque and power were more than 99.8%. This study showed that ANN was a good alternative to classical modeling techniques in terms of prediction capability for torque and power in a beta-type Stirling engine.

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